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RESEARCH PAPER

Integrating Shared Autonomous Vehicles into Existing Transportation Services: Evidence from a Paratransit Service in Arlington, Texas

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Abstract

This study investigates the potential benefits of integrating shared autonomous vehicles and an existing transportation system by exploring a recently initiated project that integrates autonomous vehicles (AVs) with an existing on-demand ridesharing service, Via, in Arlington, Texas. We first identified the spatial patterns of the ridership on a localized scale, using geographically weighted regression (GWR) for the existing paratransit service, Handitran. Assuming that the existing ridership will be combined in the future with shared autonomous vehicles, we looked at integration options, based on the spatial patterns of supply and demand and payment options for the riders. The results suggest that the paratransit service, Handitran, is currently used by a small proportion of the eligible population, whose travel patterns differ based on their age. For instance, younger users usually ride Handitran for traveling to work, recreational activities, and routine chores, while senior riders often use the service for medical and recreational trips. The results of the GWR model indicate that the major determinants of Handitran usage are the population's percentage of older adults, racial distribution, and household vehicle ownership; the coefficients of these factors vary across the city. Hot-spot analyses' results reveal that integrating the services will improve the efficiency of the existing transportation system by responding to the excess rider demand, particularly in the downtown area. Finally, we describe the implications of implementing policies for AV integration for cities, service providers, and other stakeholders and suggest future research topics.

Keywords Shared autonomous vehicles · Paratransit · Geographically weighted regression · Integrated mobility · Mobility as a service

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1 Introduction

Alleviating the need for owning a vehicle and promoting the use of public transit may be simultaneously accomplished by integrating transportation services [1]. Several studies have proposed combining fixed-route transit systems in dense areas with demand-responsive services that serve those in less transit-demanding locations [2–5]. Recently, transit agencies have partnered with rapidly growing, privately owned transportation network companies (TNCs) that use an online platform or mobile application to connect commuters with drivers who are operating their own vehicles [9] in an attempt to combine multiple mobility modes, increase the cost-effectiveness of travel, and provide more options for existing and future transit users [6]. Sharing repetitive and pre-planned trips through on-demand services reduces the number of miles traveled and the length of time required to reach destinations compared to conventional ridesharing services such as taxis [7]. Therefore, partnering with mobility-on-demand (MOD) companies to integrate public transit into TNCs enhances the efficiency and quality of public transport services, particularly for low-income, elderly, and disabled people and those who reside in rural areas [8]. Although various studies have explored integrating fixed-route transit and demand-responsive services, discussions about integrating future technologies such as shared autonomous vehicles (SAVs) into existing public transit services are still limited [9–11], despite their promising potential [12, 13]. Recent literature on the potential synergies between AVs and ridesharing touts SAVs as having unique advantages over other public transit modes, such as lower travel costs and more trips served per ride [12], greater travel convenience [14], and the ability to mitigate adverse environmental effects [12]. A rich body of research addresses factors contributing to the deployment and adoption of AVs; however, most of them assume that AVs are an updated version of personal human-driven cars [15–19]. Rapid advancements in the field of information and communication technology (ICT) equip AVs with a much higher potential than a personal automobile for enhancing mobility options and reducing manual driving efforts, and the interactions between existing transportation services and future SAVs need further exploration.

To address the research gap, we explored the potentials of an integrated transportation network, including an SAV and an existing paratransit service. Our focus was on RAPID (rideshare, automation, and payment integration demonstration), a SAV project that aims to integrate level 4 AVs into existing transportation services in Arlington, Texas. The RAPID project combines AV and MOD technologies to develop an efficient and accessible transit network in a low-density urban setting where conventional fixed-route transit is impractical. The project also provides wheelchair-accessible vehicles as part of its autonomous fleet. The ways that the SAVs can play a complementary role in their integration with the existing on-demand ridesharing paratransit service were explored, as were the spatial patterns of trips at a block group level. Sociodemographic factors were controlled using geographically weighted regression (GWR) techniques to identify local and spatial differences while exploring travel patterns. Block groups are the smallest geographical scale used in such a study to the best of our knowledge, giving more targeted and local transportation insights. Most of the previous research was developed based on aggregated data at relatively large geographical scales where multiple modes of public transit are available (e.g., counties, cities, census tracts), but studies of midsized cities with no fixed-route public transit option are currently lacking [18, 20, 21].

The remainder of this paper is organized as follows. Section 2 describes the conceptual framework of transportation integration while addressing the features of SAVs and paratransit services in the existing literature. The research methodology follows and iterates the details of the case study, followed by descriptions of the data collection and analysis. In the results section, we detail the significant findings, and in the discussion and conclusion section, we summarize the results and potential policy implications.

2 Literature Review

During the last few decades, designing and operating an integrated public transit system has become a subject of great interest [20, 22, 23]; however, studies on the integration of AVs into existing transportation services have only been conducted recently. The first efforts to study AVs as a potential enabling technology for improving future urban mobility researched systematic approaches to design and evaluate autonomous mobility-on-demand (AMoD) systems. To estimate the effects of different SAV fleet sizes and environmental benefits regarding the relocation of self-driving shared vehicles with personal mobility, transportation scholars often utilized agent-based simulation models and espoused that a reasonable fleet of SAVs has the potential to replace conventional vehicles [12, 24]. For instance, Spieser et al. [25] suggested that deploying a fleet of SAVs the approximate size of one-third of all personal transportation can meet an entire population's mobility needs.

Synergistic opportunities between AVs and public transit systems differ based upon the City's organizational structure and demand characteristics. In Singapore, Shen et al. [10] proposed preserving bus routes in high-demand areas while replacing low-demand bus routes with shared AVs. They developed an agent-based supply-side simulation, and the results indicated that a combination of 90% high-demand bus routes with 10% AVs could improve the service quality, sustainability, and efficiency of existing bus services. The result of a study by Levin and colleagues [9] indicates that integrating a transit service with a small fleet of SAVs can reduce the transportation system's total travel time. Another agent-based simulation of the supply and demand interactions of an integrated AV and public transit system in a major European city revealed that suppliers should consider the level of service and the operational cost to achieve an optimal fleet size. Some strategies, such as combining AV and public transit fare systems, encourage the demand for ridesharing and reinforce service integration [11]. Exploring the economic impacts of substituting conventional buses with demand-responsive transit (DRT) services in low-to-medium density areas indicates that service fare and vehicle capacity can determine the demand for new service integration [26]. In summary, factors such as the fleet size and vehicle capacity; the quality and the level of the service, the fares charged, operational costs, hailing strategies, transit frequency, and fleet management are among the factors that have been studied to understand the balance between public transit and SAVs through simulation of SAVs system platforms [11, 27–29].

The studies mentioned above proposed a simulation-based approach to designing and evaluating integrated AV and public transportation systems. A few studies have also explored the potential of AVs to resolve transportation issues by integrating solutions, while analyzing the social dynamics, social preferences, attitudes, and consumer concerns [18, 30, 31]. A recent study suggests that for efficient and economic integration of public transit services into on-demand ride-sourcing services, there is a need to understand factors affecting riders and drivers' travel demand and supply in an integrated system [32]. The results from an empirical study in Atlanta showed that the residents would be interested in integrating their high-quality mass transit with AVs if they felt that such integration could improve their trip time and productivity [18]. A recent study suggests that accessibility and safety are the primary concerns of people considering adopting an integrated transportation system [33].

A substantial gap remains in the synergistic opportunities provided by AVs and existing transportation services. As cities and transportation agencies begin to integrate and improve their transit services, it is crucial that they understand the travel patterns and factors that influence the existing ridership that is expected to utilize SAVs. Successful policy development for integrating transit services requires recognizing the travel behavior and patterns of the services that are expected to operate through the system.

Past studies have been primarily conducted in large cities with ample public transit access, such as Singapore, Lisbon, and Toronto [21, 24, 34, 35], but defining the role of SAVs in future transportation systems is different in urban settings with no access to a comprehensive and robust public transit service. Accordingly, this study aims to understand the patterns of existing usage and potential interaction between an SAV fleet with an existing ridesharing service by answering the following questions:

1. How and to what extent is the existing paratransit service currently used by the residents of a city?
2. What forces shape the existing ridership at the block group level?
3. What opportunities can be considered a result of the potential integration of SAVs into the current service?

We examined the travel behaviors of the users of Handitran, specialized paratransit service in Arlington, Texas, to begin answering the questions, as the RAPID SAV is projected to operate in areas currently served by Handitran: downtown Arlington and on the University of Texas at Arlington campus. We compared the usage patterns of the Handitran service inside and outside the proposed RAPID SAV service area to predict the possible demand and ridership patterns for the new service. This study will help AV planners predict SAV service usage by identifying the paratransit service's actual users and understanding the SAV–paratransit interaction will enable the City's administration to make data-driven decisions and further optimize the existing services and the proposed SAVs. To perform our study, we used trip data from the Handitran service for all rides requested during 2019.

The Handitran riders were categorized into two groups: adults above the age of 65 and persons under the age of 65 with disabilities. This population segment was addressed as the transportation-disabled population and was studied, using a wide range of techniques that varied from focusing on the demographic characteristics of travelers to spatial and geographic factors that influence the traveling behavior of the elderly [36–40]. We then compared the Handitran usage patterns inside and outside the RAPID service zone and explored the factors affecting the paratransit ridership to predict the future integration of the SAV ridership. The differences in trip characteristics when an alternative mode of public transit is available, and the potential integration of the future SAV service into the current paratransit service were investigated. While previous research mainly relied on regression models to identify transit ridership determinant factors, this study utilized a GWR model to evaluate the spatial ridership of Handitran paratransit service.

3 Data and Methodology

3.1 Data

3.1.1 Study Area

This study was conducted in the City of Arlington, Texas, which has the distinction of being one of the largest cities in the United States without a mass-transit service [41]. Arlington is a medium-sized city that is located in the middle of the DFW metropolitan area, which is considered one of the fastest-growing metro areas in the United States. The 2019 population of Arlington was 392,462, a 7% increase from 365,438 in 2010 (ACS-2019). The number of people aged 65 or older was 40,101 (10.2% of the total population) in 2019, up from 29,752 (8.1% of the total population) in 2010 (American Community Survey 2019). Due to its strategic location in the heart of the fast-growing DFW metro area, population growth is expected to continue.

Arlington's leadership role in implementing app-based, on-demand services and SAV technologies in the Dallas Fort Worth (DFW) region made it an attractive location in which to perform this research and analyze the potential integration of SAV services with existing transit options. It has an app-based, on-demand ridesharing service under the Via[1] platform and is also served by the Handitran paratransit service [42]. In 2020, the City was granted a $1.7 million Integrated Mobility Innovation (IMI) award by the Federal Transit Administration (FTA, 2020). While some findings may not be directly applicable to cities of all types and characteristics, this study provides valuable insight for cities of comparable size and demographics.

3.1.2 Handitran Service and Trip Data Analysis

Arlington's Handitran is a federally assisted transportation program under Title VI of the Civil Rights Act of 1964 and related statutes that provide rides to eligible people (City of Arlington Handitran, 2014). Handitran rides can be booked online via the website or by telephone. To be eligible for the service, an individual must be either a "senior citizen" or "transportation disabled." Senior citizens are defined as persons 65 years of age or older; the transportation-disabled are those who, because of a functional limitation (caused by either a physical, medical, or mental condition), cannot independently operate a motorized vehicle, either on a permanent or temporary basis.

Handitran is an important mobility option that serves the entire City of Arlington and includes up to 1.5 miles outside the city limits. The downtown area will be served by an SAV service (RAPID) that will be integrated with the on-demand ridesharing service (Via). We used a dataset based on all the Handitran rides requested during 2019 to explore the characteristics and features of the service. Figure 1 shows the distribution of trips based on their points of origin. In 2019, there were 373,202 trips requested from Handitran, including trips that were cancelled or not taken, with an average of 231 trips per passenger.

3.2 Analytical Methods

The data analysis was performed in three steps. First, we analyzed the trip data for Handitran, a service for the transportation-dependent population in Arlington, to disaggregate the riders and gain a better understanding of the occasional and frequent users of the paratransit and to determine how the different categories of riders use the service. Second, we used the GWR technique, which explores relationships between paratransit ridership and sociodemographic and geographical features at an aggregated level, to explore the determinant factors of ridership for Handitran. Finally, we evaluated the potential for integrating the paratransit service into a newly initiated SAVs service in Arlington.

3.2.1 Trip Data Analysis

The trip level data for all the trips requested from the Handitran service in 2019 was analyzed, based on the age of the users, to determine the role, if any, that age plays in the usage patterns. We also analyzed the travel patterns for which the Handitran services were requested, based on the time of day and purpose of the trips.

3.2.2 Geographical Weighted Regression (GWR)

For analyzing the determinant factors of the ridership, we used a GWR model, which was more effective than a linear regression model. Linear regression models are beneficial for understanding relationships between dependent and independent variables, but they generally do not consider the effects of geographical or spatial variations [6] in the model. Sociodemographic characteristics play a crucial role in shaping transit usage behaviors and patterns, but their spatial features vary across geographical areas.

Geographically weighted regression models, which account for spatial non-stationary of variable values over space in a model, were first proposed by Brunsdon et al. [8]. They are an extension of linear regression models, as they account for spatial variations. The GWR model can be mathematically described as shown in Eq. (1). GWR is a

[1] An app based, on-demand ride service providing shared rides at subsidized rates in the City of Arlington, TX.

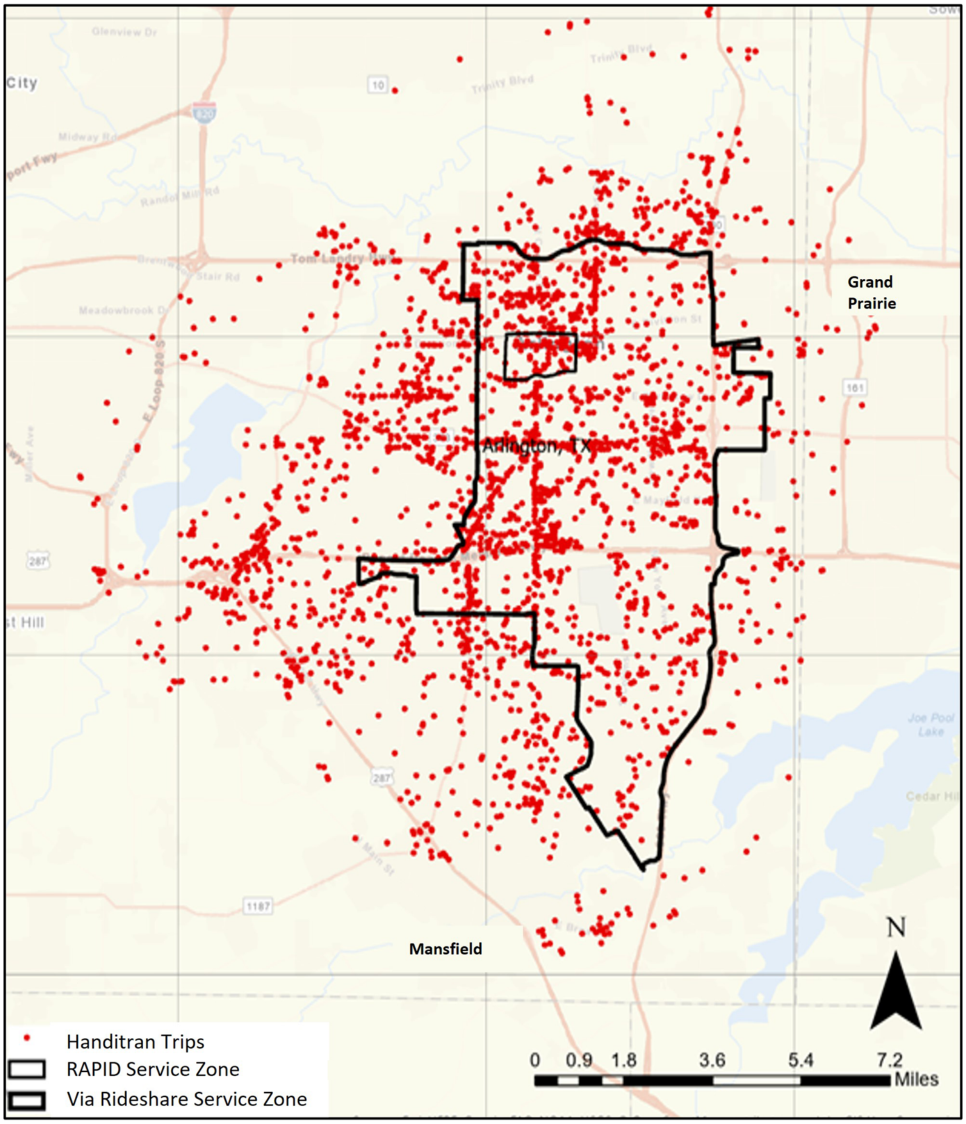


Fig. 1 Spatial distribution of trips completed by Handitran in 2019

popular analytical technique that is used in the literature to explore local-scale variations in variables of interest [43–46]:

$$y_i = \beta_0(u_i, v_i) + p\sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i, \tag{1}$$

where (u_i, v_i) are the coordinates (latitudes and longitudes) of a location, β_k represents the parameters that need to be estimated, is a function of the location, and is calculated for each spatial unit (block group in this analysis), εi is the error term.

To find a model with a better fit, we ran ordinary least square regression (OLS) and GWR, using the same set of predictor variables; the number of Handitran rides was used as the dependent variable. The OLS regression model resulted in a very low R-squared value (0.20), and the residuals plots showed a clustering behavior. Therefore, we chose GWR because of its higher R-squared value and random residuals and for its ability to explain variations at a local scale [47, 48]. The spatial statistics tool in the ArcGIS Pro software was used to run the GWR model.

Seven sociodemographic variables at the block group level were found to be significant in the GWR model: total population; percentage of population 65 and older; distribution of white, Asian, and non-English-speaking people; share of people with bachelor's or higher degrees; and the share of households without a vehicle. The data for these variables were collected from the 5-year American Community Survey (ACS) at a block group level and was validated by the pairwise correlation test.

We chose block groups as the spatial unit of analysis for several reasons. First, they are the most granular

Table 1 Handitran trip data summary (2019)

Attribute	Data
Total population in Handitran zone	573,867
65 + Population (ACS-2014–2018) without disabilities	35,368
People with disabilities	57,386 (10% of the overall population has disability: City of Arlington)
Eligible people	92,754
Total users	1618 (~ 1.74% of eligible users)
Total trips	373,202
Average trips per user	231
Only 12% of the users make over 50% of all trips	

Table 2 Summary of trip data by age group

	Age group		
	Under 65	Over 65	Total population
Users			
Number of users	422	277	699
Percentage	60	40	100
Trips			
Total number of trips	75,580	30,206	105,786
Percentage	71	29	100
Average number of trips	179.10	109.05	151.34

geographical level for which census data is available from the American Community Survey, and they are more analogous to neighborhoods than census tracts. Second, our study area is the City of Arlington, which is a mid-size town and consists of 32 census tracts and 355 block groups. Considering a higher spatial unit of analysis such as a census tract would reduce the number of observations and result in a lack of variation in the key variables within the case study area for running a regression model. Third, block groups have been extensively used in the literature where the research questions involve variables related to sociodemographic characteristics [49–52].

4 Data Analysis and Results

4.1 Trip Data Analysis

4.1.1 Handitran Travel Pattern

Research shows that paratransit services do not operate at their maximum capacity, mainly because of the lack of coordination between paratransit agencies and contractors hired to provide the services [53]. Table 1 shows the usage patterns of the Handitran service in 2019. Only 1618 customers used the service, which is less than 2% of the population eligible for the service, based on their age or disability status. Not only is the number of active users low, but most of the trips were taken by an even smaller number of users. Data show that over 50% of all Handitran paratransit rides in 2019 were made by only 12% of its users. The limited use of Handitran service by the eligible population could stem from the quality of the service and hailing and fare strategies. In addition, the service is not available to all potential users due to the fleet size, capacity of the service, and the hailing strategies set by the Handitran management. Another reason for the low usage could be the lack of advertisement for the services, which leaves many unaware of the option. It is also highly likely that many of the eligible users do not know about the service or know how to use it due to the lower educational attainment levels and lack of English-speaking skills.

Table 3 *T* test for trip distances of two groups

Two-sample t test with equal variances						
Group	Observations	Mean	Std. Err.	Std. Dev.	[95% Conf. interval]	
Under 65	75,580	6.780989	0.015088	4.147858	6.751418	6.810561
Over 65	30,206	6.075029	0.022283	3.87279	6.031353	6.118705
Combined	105,786	6.57941	0.012556	4.083662	6.554802	6.604019
Diff		0.70596		0.027713	0.651642	0.760278
H_a: diff < 0			H_a: diff $\neq 0$		H_a: diff > 0	
$Pr(T < t) = 1.0000$			$Pr(\|T\| > \|t\|) = 0.0000$		$Pr(T > t) = 0.0000$	

Table 4 *T* test for trip durations in two groups

Group	Observations	Mean	Std. Err.	Std. Dev.	[95% Conf. interval]	
Two-sample *t* test with equal variances						
Under 65	75,580	18.62929	0.030948	8.508019	18.56864	18.68995
Over 65	30,206	16.8618	s0.047864	8.318655	16.76798	16.95561
Combined	105,786	18.1246	0.026109	8.491951	18.07343	18.17578
Diff		1.767494		0.05755	1.654697	1.880292
H_a: diff < 0			H_a: diff $\neq 0$		H_a: diff > 0	
$Pr(T < t) = 1.0000$			$Pr(\lvert T\rvert > \lvert t\rvert) = 0.0000$		$Pr(T > t) = 0.0000$	

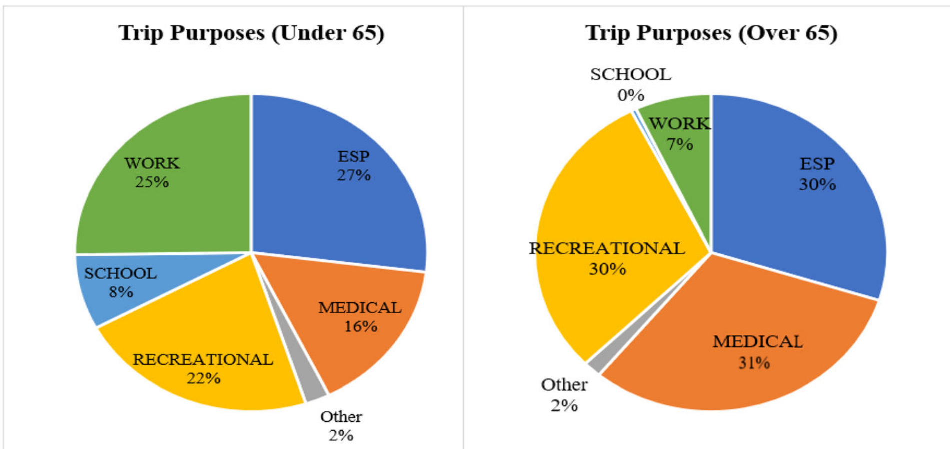


Fig. 2 Trip distribution by purpose

4.1.2 Trip Characteristics by Age Group

Some studies suggest that the frequency of trips requested by individuals decreases after age 65 [54]. Table 2 shows the distribution of users in each age category (over and under 65), the total and the average number of trips using Handitran data. Overall, the ridership is significantly high in the group under 65 years of age. This could be associated with the purpose of each age group using the service. 25% of their Handitran trips by younger users are work-related, while only 7% of trips by older users are for work purposes. This could be one of the reasons for higher trip frequencies by younger users.

To evaluate whether the travel patterns of the two groups (over and under 65 years of age) are statistically different, we ran a difference in means test (*t* test) for trip distances and trip durations for both groups. The results of the test, shown in Table 3, revealed that there is a statistically significant difference between the trip distances of the two age groups; the hypothesis that the differences are not equal to 0 is statistically significant at a 95% confidence level.

The results of the t test for trips durations for both age groups are shown in Table 4. It can be observed that there is a statistically significant difference in the trip durations of the two groups, with younger people taking longer trips on average.

4.1.3 Trip Purpose by Age Group

Figure 2 illustrates the distribution of trip purposes based on the two age groups. The trip purposes for the Handitran paratransit are categorized as work, school, medical, essential personal trips (ESP), such as going to a bank, grocery store, pharmacy, etc., and recreation. The results indicated that there is a notable difference between the two age groups' purposes for their trips. The pie chart shows that users under 65 make a higher share of work- and school-related trips, while older users make more medical and recreational trips.

4.1.4 Temporal Patterns by Age Group

In addition to the aforementioned trip characteristics, it is important for the optimal allocation of resources to

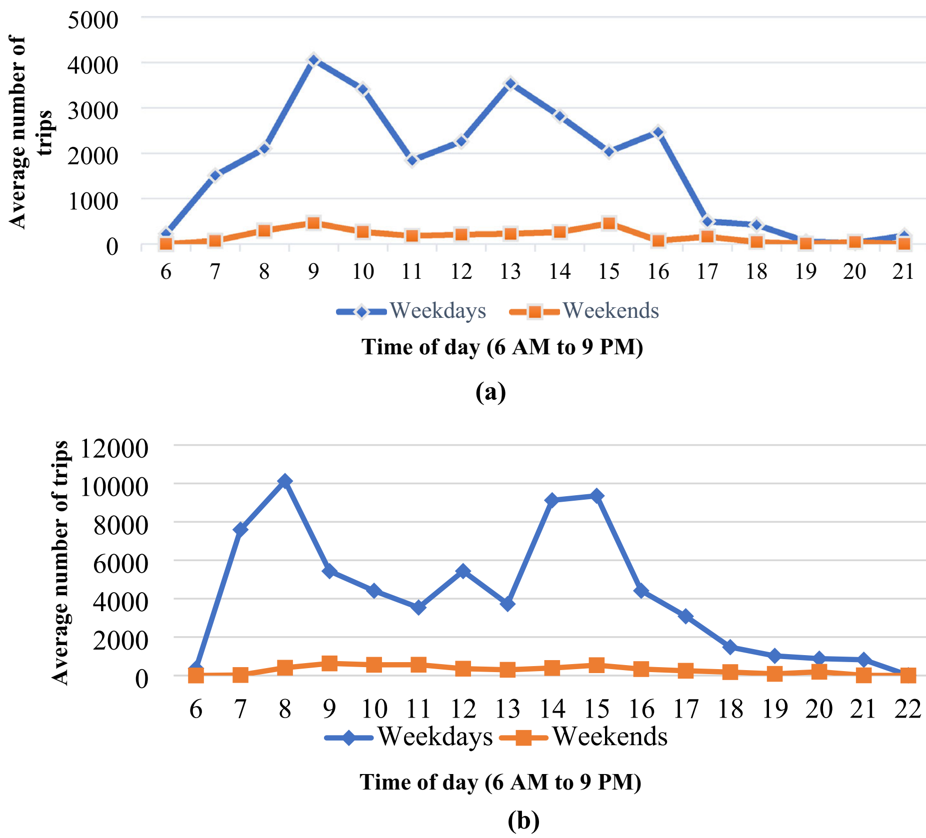


Fig. 3 **a** Temporal distribution of daily average number of trips made by users 65 years of age or over. **b** Temporal distribution of daily average number of trips made by users under 65 years of age

understand the distribution of trips pertaining to the time of the day. Understanding the temporal usage patterns of the Handitran service is vital to uncovering certain characteristics of passengers' daily activities and the potential for integrating multiple services, such as the new SAV RAPID service. Such temporal usage patterns can be effectively understood via a graph, as illustrated in Fig. 3. The plots in Fig. 3a, b display the temporal patterns of usage for both age groups and further divide the usage into two categories: weekdays and weekends. The plots show the number of rides taken on Handitran during the operating hours (7 a.m. to 10 p.m. on weekdays; 8 a.m. to 9 p.m. on Saturdays).

There is a clear difference in the temporal usage patterns of the two age groups and days of the week. During weekdays, users tend to make more trips in the early morning, with peak usage between 8 and 9 a.m. for both age groups. During weekends, the trips peak almost 1 h later (9 and 10 a.m.) than on weekdays for both age groups. Evening peaks vary widely between the age groups and the two temporal categories. Evening peaks tend to last longer during weekdays, starting at 1 p.m. for older users and 2 p.m. for younger users. The plots also show that younger users take advantage of the service more frequently than older users; in fact, they made more than 10,000 trips on average during peak hours, while older users averaged slightly more than 4000 trips per day. These temporal patterns correspond, to a large extent, to trip purposes for each group. As younger users take Handitran trips for work, the peak hour for these users is between 7 and 9 a.m. in the morning. On the other hand, the peak hour for older people is between 8 and 10 a.m. indicating that older people start their daily activities later in the day than younger people.

Table 5 Descriptive statistics of variables in GWR model

Variable type	Variable	Mean	SD
Dependent variable	Number of Handitran rides	221.3	286.9
Independent variable	Total population	1764	1070
	Share of 65 and above	10.9	8.03
	Share of white population	62.7	22.3
	Share of Asian population	5.7	7.7
	Share of bachelor's degree/more	27.5	17.6
	Share of HHs with no vehicle	4.5	6.5
	Share of Non-English speakers	30.3	17.6

Table 6 Summary of the GWR model

Analysis details	
Number of features	335
Dependent variable	Number of Handitran trips
Explanatory variables	Total population
	Share of 65 and above
	Share of White population
	Share of Asian population
	Share of bachelor's degree or higher
	Share of households with no vehicles
	Share of non-English speakers
Model diagnostics	
R-squared	0.59
Adjusted *R*-squared	0.45

4.2 Results of the GWR

The GWR model was used to analyze the determinant factors of ridership for the Handitran service. Descriptive statistics for the variables are presented in Table 5.

Table 6 shows the output of the GWR model. The GWR-adjusted R-squared value of 0.44 is twice that of the OLS model. The GWR model evaluated each element (block group) at a local scale in relation to its neighbors. Neighbors were the block groups with similar characteristics that were spatially located next to the block group under study. This process was performed for each block group, and a coefficient was assigned to every unit.

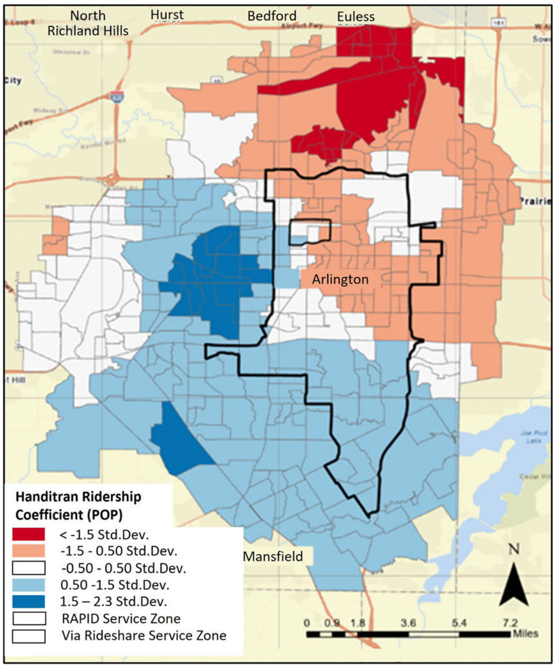
Figure 4a–g shows the distribution of the coefficient values of all the independent variables, with the dependent variable at the block group level. The large and small polygons represent the Via and RAPID service areas, respectively. The local-scale maps from GWR allow us to understand the type/strength of the relationship of the variables, with independent variables at a micro (block group) scale. We anticipated that understanding the determinants of the existing ridership by considering spatial differences would help in devising relevant strategies for integrating the new transportation service. The small and big polygons show the Handitran and RAPID service areas, respectively. Because of variations in the absolute values of coefficients, we used a standard deviation scale for easy comparison of the independent variables. The red color represents statistically significant negative coefficient values, indicating that the relevant variable has a negative relationship with Handitran ridership. The darker red color shows higher (negative) coefficient values, while the lighter red/orange color shows lower negative coefficient values, ranging from − 0.5 to − 2.5 standard deviations. The blue color represents statistically significant positive coefficient values, showing a positive relationship of the variable with Handitran ridership. The dark blue color represents higher coefficient values, while the light color shows lower values ranging between 0.5 and 2.5 standard deviations. The white color represents values between 0.5 and − 0.5 standard deviations, where the relationship between the independent variable with the number of Handitran Trips is not statistically significant. The maps show that the coefficients of all independent variables are not globally uniform but vary significantly in different parts of the City, indicating different usage patterns. Variations in coefficient values across spaces are given in Table 7.

5 Potential for Service Integration

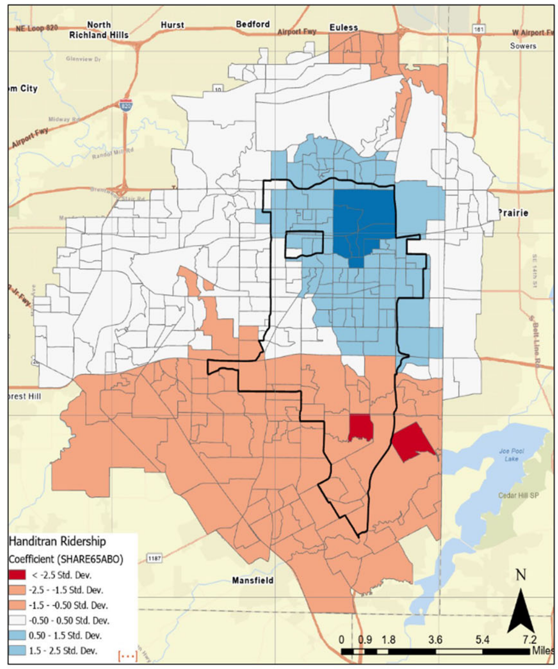
In recent years, the transportation sector has experienced technological advancements, new modes of transit, and increasing growth of app-based on-demand ride services. The improvement of transit services and provision of a better mobility experience are possible through integrating multiple modes in terms of ride-booking options (smartphone apps) and modes of payments (online payment for services). Integration of the two systems could likely improve the quality of service, provide a better mobility experience to users, reduce traffic congestion, enhance the overall system performance, and lower the operating and maintenance costs. Based on the existing usage patterns, we find the following advantages to integrating multiple modes to improve the overall system.

5.1 Ridership/Clientele

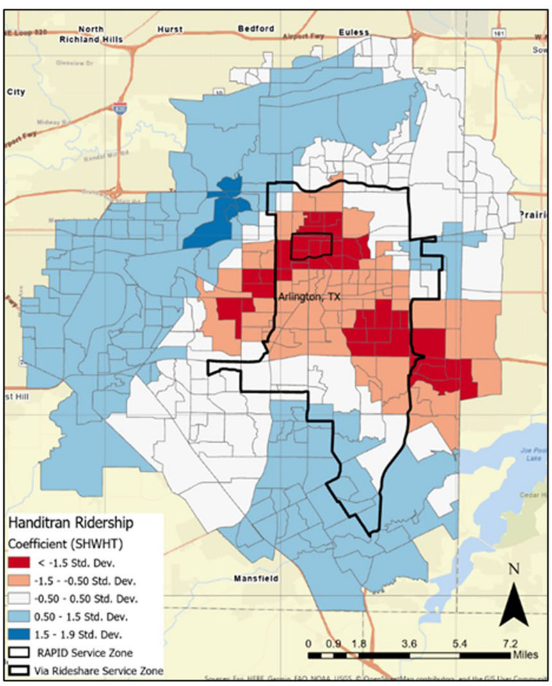
Handitran provides services for the entire City of Arlington, while the proposed Arlington RAPID services will only be available in the areas in and around the UTA campus and downtown. Although the service area for RAPID is minimal compared to Handitran (about 1% of the total Handitran service area), it will serve some of the City's largest activity centers. Since the population of the RAPID service area is unknown, we used the number of Handitran trips per square mile to compare the usage patterns and as a proxy for the future demand and potential of integrating both services. As shown in Table 8, the number of trips per square mile in the RAPID service area was about 28% larger than that of the whole Handitran service area in 2019. Hence, there is considerable excess demand for using Handitran in the designated RAPID service area. Accordingly, the RAPID integration could improve the



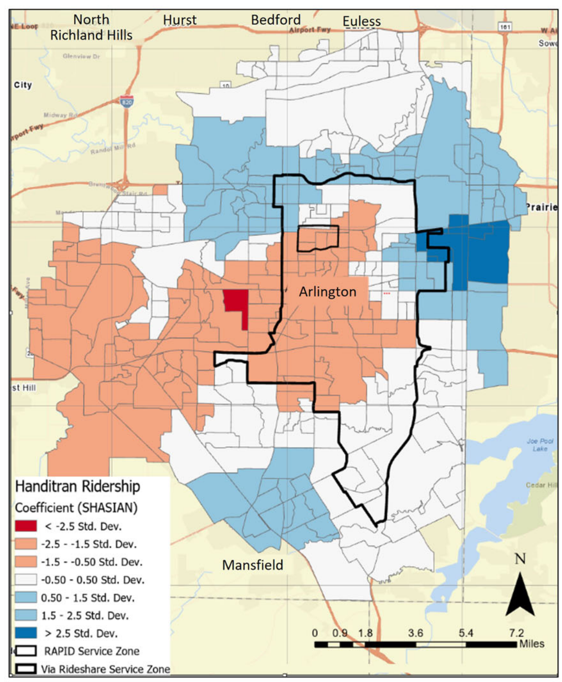
(a) Total population



(b) Share of 65 and above



(c) Share of White population



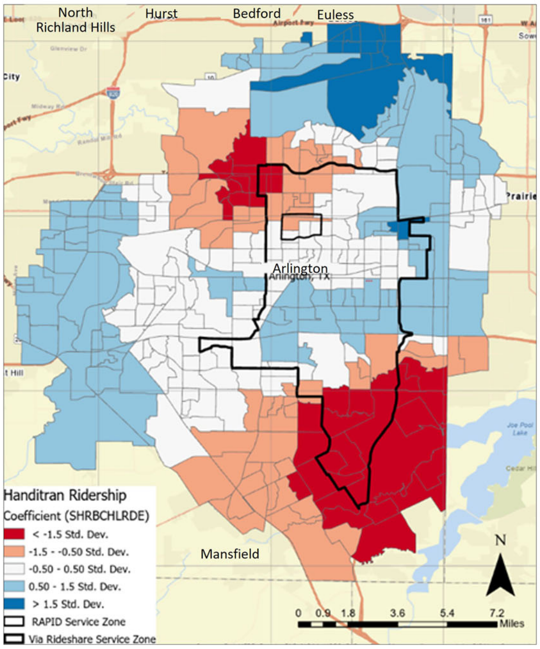
(d) Share of Asian population

Fig. 4 a–g Local coefficient values of independent variables vs. the dependent variable (number of Handitran trips per block group); color scale shows the value of each coefficient

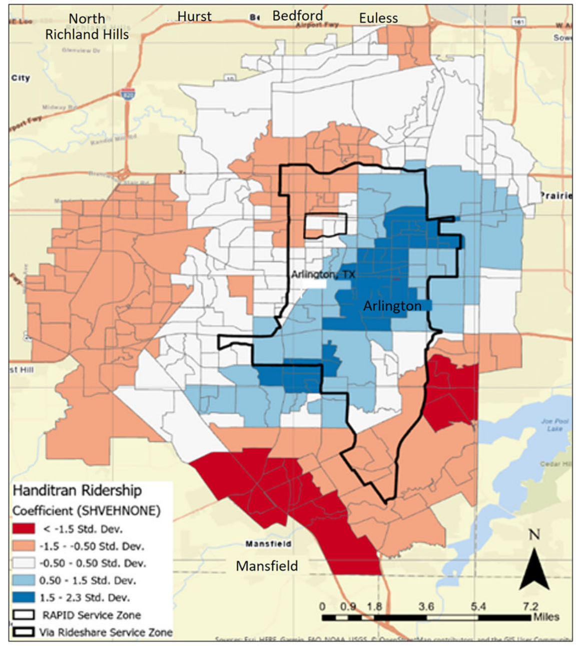
efficiency of Arlington's existing transportation system by servicing the excess demand for ridership in the City's downtown area.

5.2 Existing User Locations

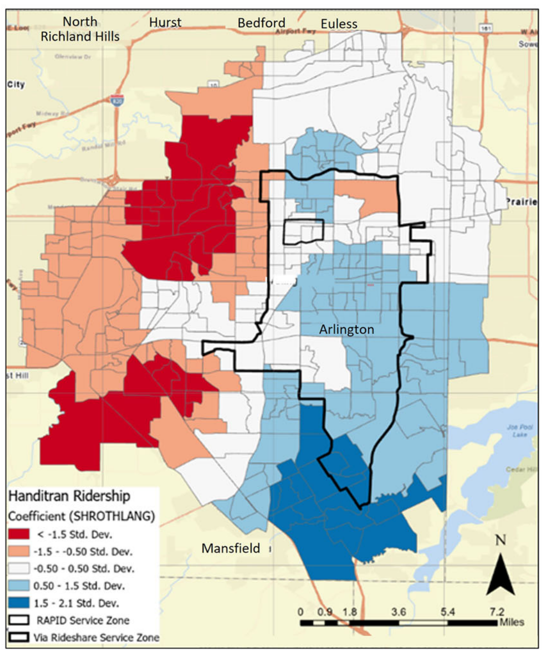
The RAPID project is projected to include a wheelchair-accessible vehicle to provide services to people with disabilities. To understand the potential for transit demand



(e) Share of bachelors or higher degree



(f) Share of households with no vehicles



(g) Share of non-English speakers

Fig. 4 continued

from the perspective of the transportation-disabled population, we used ArcGIS software to run an optimized hot-spot analysis of Handitran users, based on their home locations, comparing hot and cold spots with the proposed RAPID service area, The results are shown in Fig. 5. The black polygon shows the proposed RAPID service area, the red color shows the users' hot-spots, and white indicates that there are not spatially significant hot-spots. It is clear from the map that Handitran users are clustered in the downtown/UTA area, and the hot-spots are partially located within and surrounding the RAPID service zone, indicating a higher demand for paratransit services.

Table 7 Variation in coefficient strengths across space

Variable	Spatial variation in relationship with Handitran ridership		
	Strong	Neutral	Weak
Total population	South	West	North
Share of 65 and above	Center	West, east	South
Share of White pop	Northwest, south	Northeast, southwest	Center
Share of Asian population	East, northwest	North, south	Center, west
Share of bachelor's degree/more	West, northeast	South, northwest	Center
Share of HHs with no vehicles	Center	North	South, west
Share of non-English speakers	West, northwest	Northeast	South, southeast

5.3 Existing Demand Distribution and Future Extension Potential

While it is important to know that many of the Handitran users are clustered in the downtown area, it is also important to see their usage patterns based on the spatial distribution of the number of trips. Intuitively, it seems that trips should be clustered in areas where users are; however, the hot-spot analysis of the trips showed a different pattern. Figure 6 shows the results of the hot-spot analysis of trips based on their origins. We used Maptitude, a spatial analysis software, rather than the ArcGIS-optimized hot-spots option, to run the analysis for origin points of trips, as ArcGIS requires that the features be aggregated to a polygon. For example, it uses the number of trips per block/block group to create a hot-spot map, while we opted to run hot-spots based on actual trip locations. Small and big polygons show the RAPID and Via on-demand service areas, respectively. The red areas show hot-spots, and the blue areas show cold spots. Hot-spots show spatially significant clustering of high values, while cold spots show spatially significant clustering of low values (in this case, the number of Handitran trips). These hot-spots show that although many Handitran users live in the downtown area, most of the trips originate from the southern part of the City. We also see a major effect of the Via service, because all the hot-spots are located outside the Via service area. These patterns show the inter-dependence of multiple services and the potential for integration because all the services currently operate individually while competing with other services. The trip hot-spots data could also be useful for the future expansion of the RAPID service area.

Table 8 Comparison of Handitran service usage within and outside of RAPID service area

Service zone	Total area (sq miles)	Total completed trips in 2019	Trips per square mile
Handitran (existing)	199	149,012	1410
RAPID (proposed)	1.09	1,972	1809
% Of RAPID	1.04	1.32	128.3

5.4 Interaction with Alternative Transit Modes and Service

Unlike other cities of the same size, Arlington does not have a fixed-route public transit system. At present, Handitran only serves the transportation-disabled and elderly populations, while the Via on-demand rideshare service is available to anyone in the City. As of 2019, Handitran served the entire City of Arlington, plus 1.5 miles outside the city boundaries, while Via's service area was limited to specific sections of the City.[2] Therefore, it is important to understand the interactions of paratransit services with other public transit modes—Via, in this case.

Table 9 shows a comparison of Handitran trips in areas where Via is and is not available, and it is evident that people who reside in areas that do not have Via services take more and longer trips on Handitran. The statistics show that 62% of Handitran trips originate from areas where Via services are unavailable; only 37% originate from block groups served by Via. These statistics show how the unavailability of an alternative mode impacts other modes. Without integration, both services may be present in an area but are more likely to compete rather than to complement each other. On the other hand, an integrated service can significantly improve the efficiency of all modes/services.

5.5 Potential for Payment Integration

Another avenue of integration is the payment platform for these services. Currently, Handitran payments can only be made with cash or a monthly pass. According to the service policy, no passenger can be denied services for his/her inability to pay the fare, so a "fare-owed form" is filled out by any passenger unable to pay at the time of the ride. Those completing the form are obligated to pay later, but no data are available about how many actually do so. There is, however, data that show that cash payments and fare-owed procedures can adversely affect the quality and

[2] Via's service area was expanded to the entire city of Arlington in January 2021.

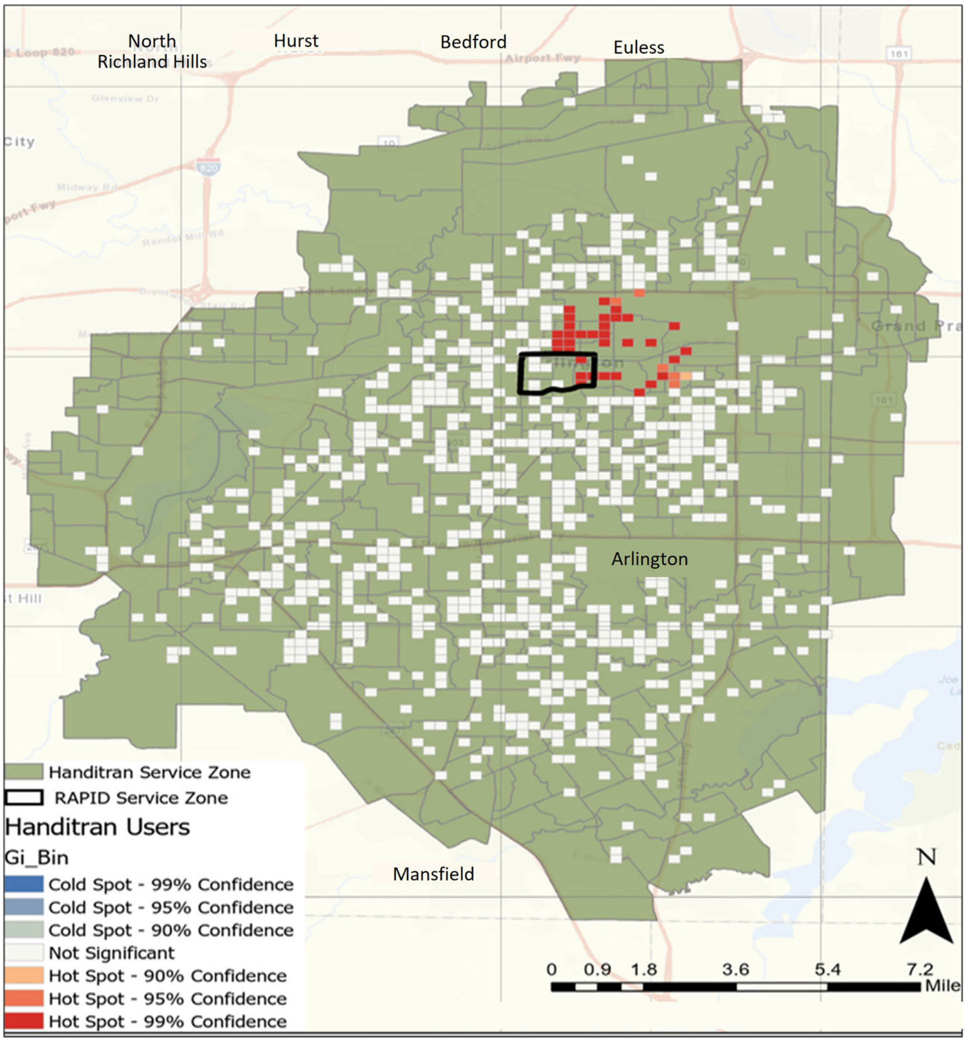


Fig. 5 Hot-spots of Handitran user locations

efficiency of the service. Table 10 shows the distribution of modes of payments for Handitran trips. Approximately 34% of trips are paid for with cash, and around 16% do not pay at the time of the ride. This payment collection system is very inefficient and results in less revenue. Since Handitran does not have an existing smartphone app or online mode of payment, its revenue collection could be enhanced if it were integrated with RAPID.

6 Discussion and Conclusion

This study explored the advantages of integrating existing transportation services and proposed a SAVs service. We focused on an existing Handitran paratransit service and the RAPID SAV project piloted by the City of Arlington, Texas. Unlike past studies that evaluated integrated AV and public transit services by designing concrete scenarios based on agent-based simulation platforms [10, 11], we explored the potential for SAV/PT rideshare integration by determining and understanding the travel patterns of paratransit users that may be the future consumers of the integrated services.

Data analysis of the ridership of Arlington's paratransit service indicated significant differences in the travel behaviors and patterns of the two studied age groups. A large percentage of the riders were shown to be younger than 65, rode more frequently and for longer distances than their older counterparts, and utilized the service more for work and school purposes than those older than 65. This finding may be due to life cycle changes and travel behavior shifts in older adults, such as retirement [55], and their need for more medical and recreational trips. While there is no direct empirical evidence to identify the potential users of integrated public transit services and SAVs, this finding could imply that younger adults are more likely to rideshare through future integrated services. This result is beyond the primary public transit integration

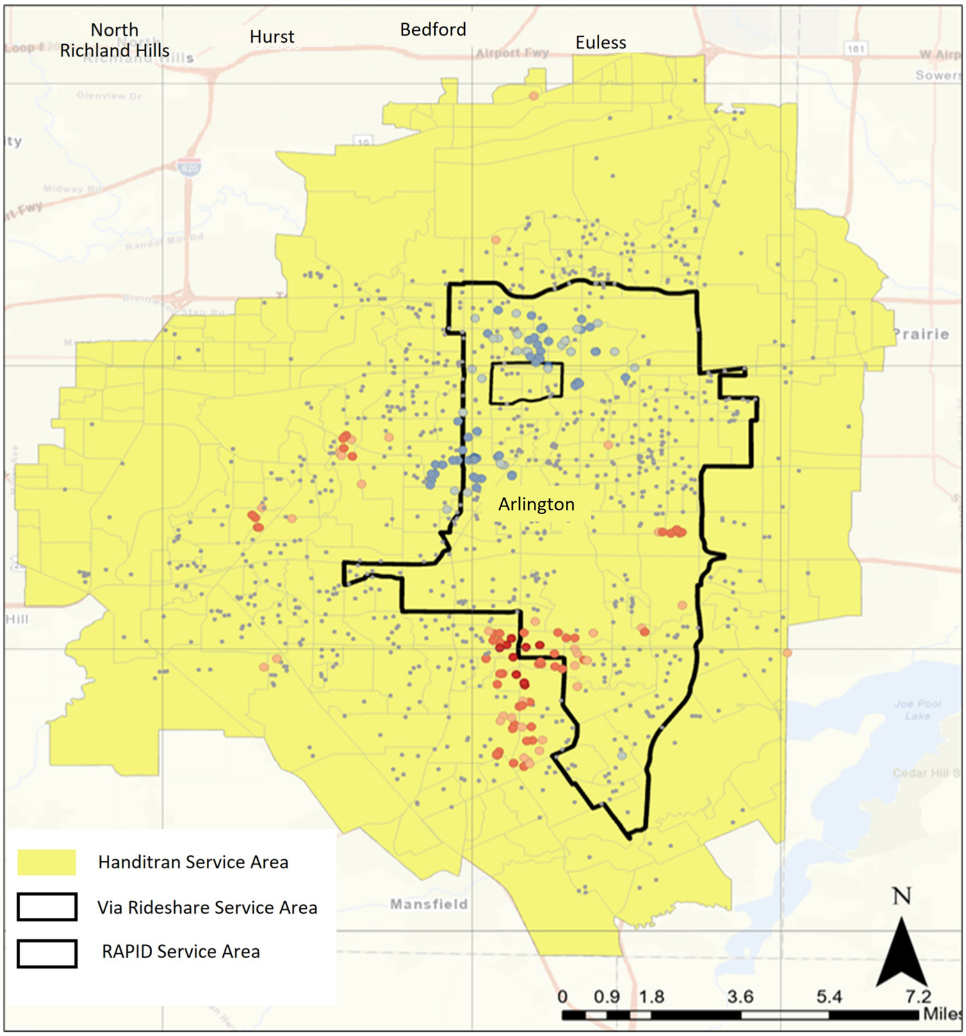


Fig. 6 Hot-spots of Handitran trips based on points of origin

Table 9 Trip comparison based on the availability of Via services

	Availability of Via services		
	NO	YES	Total
Average distance	7.13	5.36	6.46
Total number of trips	80,541	48,766	129,307
Trip distribution percentage	62.29%	37.71%	100%

As of 2019, Via served an area of 41.39 square miles, 41% of the total area of the city of Arlington

Table 10 Modes of payments for Handitran trips

Type	Share	Percentage
Cash to driver	51,825	34.78
Credit card	89	0.06
Fare owed	23,694	15.90
Monthly pass	71,726	48.14
Ticket	7	0.00
Volunteer pass	1669	1.12
Total	149,010	100.00

goals that are usually suggested to improve the mobility needs of senior adults [8]. Although it appears that the RAPID SAVs could provide a more convenient and flexible mobility option for elderly adults than driving their own vehicle, it is not possible at this time to accurately draw conclusions about the relationship between age and the adoption of SAVs. Our findings, however, do previous support studies in the US indicating that older adults are more likely to drive a private vehicle than utilize AVs [56], but younger people are more inclined to opt for an SAV [57]. Because many older adults for whom the existing paratransit services were designed do not take advantage of them, it is not expected that they will use SAVs to the extent that younger adults will.

According to the GWR results, the future RAPID service will operate in an area that shows a significant elasticity coefficient with existing paratransit in terms of sociodemographic attributes at the block group level. In the blocks in which the integrated RAPID ride will be available, race (share of the white and Asian populations) has the highest negative association with the existing ridership. The level of education (share of the population with a bachelor's degree) and lack of access to a vehicle (share of households with no vehicles) also negatively affect the existing ridership at the block level. This result reveals that in the RAPID service area, a part of the population that includes some white and Asian people with higher education and those with no access to a vehicle is less likely to use the current paratransit frequently. On the other hand, the results suggest that some RAPID service area blocks with a significant share of the 65 and above population have a greater tendency to use the current paratransit. These findings indicate the potential synergies for integrating RAPID into existing transit, including paratransit and Via on-demand rideshare, to provide services with unique advantages to residents of this particular area [12]. Although little has been done to identify t*he sociodemographic features* of potential SAV users [58, 59], our findings shed light on the findings from empirical studies suggesting that residents of densely populated regions, students, and highly trained individuals have more positive attitudes and perceptions towards AVs [60, 61].

Our findings also indicate that the deployment of SAVs and existing paratransit and ridesharing services are not mutually exclusive. A comparison of paratransit service usage within and outside the RAPID service area showed that the demand for trips per square mile in the RAPID service area was about 128% of the total trips generated per square mile across the entire Handitran service area in 2019. Despite the presence of the Via rideshare service in Arlington's downtown area in 2019, there has also been a considerable demand for using Handitran in the RAPID service area. This demand may be effectively met through the integration of RAPID SAVs by reducing travel time [9], improving service quality, and utilizing transit services more efficiently [10]. Therefore, we anticipate that the integration of the RAPID on-demand SAV service will improve the efficiency of the existing transportation system in Arlington by responding to the demand for riders in the downtown area through encouraging SAV ridesharing and improving the efficiency of all the services [11]. The high-demand hot-spots that we have identified in this work can aid city officials in determining future expansion areas for the service.

The introduction of the RAPID service in Arlington also offers opportunities for payment integration. Currently, more than one-third of Handitran service payments are made with cash, paid directly to the drivers at the time of the service. Compared to the application-based payment approaches, this method is sub-optimal and inefficient. Integration of the payment methods of the two services could offer the Handitran users more flexibility and convenience and significantly improve their trip experience.

7 Policy Recommendations and Future Research

A number of policy recommendations can be drawn from the analysis of sociodemographic determinants of ridership, spatiotemporal patterns of usage, interactions of multiple transit modes/services, and the potential for integration. These recommendations can benefit the stakeholders, the City's policy and decision-makers, and the companies providing the transit service in their planning, design, and optimization of mobility services for existing as well as future projects.

Analysis of trip characteristics and usage patterns indicate that a very small percentage of eligible users ($\sim$ 2%) use the service, and the majority of the users are younger than 65. We hypothesize this could be due to two reasons. First, many of the City's residents are not aware of the service, because it is not advertised. Second, the application process for determining eligibility takes time and effort and could be a stumbling block for those who might otherwise sign up for the service. Integration of the services and access to Handitran through a smartphone application could improve the visibility of the service and also ease the application process for new customers by providing them with an online registration facility on the app.

The temporal distribution of trips reveals that there is a higher demand on weekdays than on weekends. High demand periods during weekdays are 7–9 in the morning and 1–5 in the evening. The evening peak for older adults lasts longer than that for younger users. The spatial distribution of trips at the block group level shows a wide range of variations across the City, indicating diverse demand levels in different areas. It is expected that the distribution of vans in high-demand areas and for trips of longer durations can improve the quality and efficiency of the service; however, a simulation-based study that evaluates the distribution of resources (vans and drivers) and impacts of integration with other modes and services are needed.

Finally, the sociodemographic determinants of ridership from the GWR model suggest that the effects of sociodemographic characteristics vary significantly across the City. A variable showing a very strong relationship with ridership in the northern parts of the City may show an opposite behavior in the south. These results indicate that a strategy for optimizing the service quality in one area may not be effective in others; therefore, the City or the service providers should customize any intervention. A survey designed to reveal the preferences of potential users in specific areas could help in determining the suitability of future plans. Although this study provides a good foundation for understanding the spatiotemporal patterns of transit ridership by older adults and the likely interaction of multiple services/modes, it could be expanded in future studies by adding more sociodemographic variables and data that cover a longer period of time.

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Declarations

Conflict of Interest On behalf of all the authors, the corresponding author states that there is no conflict of interest.

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